Abstract

This dissertation presents time-series causal inference frameworks based on Markov decision processes (MDPs) and applies a customized model to analyze the effects of the COVID-19 pandemic. The frameworks assess the cumulative impact of interventions on future outcomes by comparing actual intervention actions with alternative scenarios. They are effective in evaluating both the short- and long-term effects of temporal interventions.

This dissertation is organized into three main chapters:

Chapter 2, titled "Time-series Causal Inference Using a Stationary Markov Decision Model to Evaluate Effects Over a Certain Period of Time," presents a method for time-series causal inference in single time-series data, where interventions follow a time-homogeneous policy. This approach is based on infinite MDP models, and asymptotic theory is provided for the functional approximation used in MDPs. The method allows for comparing the effects of observed interventions with those of other available interventions, whether discrete or continuous. Its effectiveness is demonstrated through simulations on various time-series scenarios.

Chapter 3, titled "Counterfactual Control Policy Evaluation in Markov Decision Processes for Causal Inference Using Kernel Estimation," presents a method for evaluating the cumulative future effects of interventions using observed trajectory data. This approach, within the framework of Markov Decision Processes (MDPs), leverages nonparametric multistep forecasting techniques to estimate future discounted response values under two conditions: the actual intervention policy and a counterfactual policy, which typically includes a specific action, such as the control action alone. This method is particularly useful for causal inference, especially in situations where implementing interventions is difficult.

Chapter 4, titled "Analyzing the Impact of Mobility Restrictions and Vaccination Rates on COVID-19's Effective Reproduction Number Using Markov Decision Process Models," applies MDP models to evaluate the impact of two key infection control measures—mobility control and vaccination—on the COVID-19 effective reproduction number. The analysis shows that mobility control consistently reduces infection spread, while vaccination is most effective initially but loses its effectiveness over time, particularly as mobility increases. The findings suggest that lifting mobility restrictions after vaccination may weaken long-term control efforts.

Overall, this dissertation contributes to the understanding and application of MDP-based time-series causal inference methods, offering practical tools for evaluating intervention policies and providing valuable insights for both theoretical development and real-world decision-making.